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VALUATION OF B2B SAAS STARTUPS -

WHAT INFORMATION AND METRICS ARE VALUE RELEVANT?

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Abstract

The valuation of early-stage startups is critical in venture capital. This thesis examines whether metrics, investors apply to assess B2B SaaS startups, can explain the probability of receiving funding and pre-money valuation. Empirical results from 441 fundraising attempts of startups support the key hypothesis that investors consider specific metrics and value information provided by startups. More specifically, this thesis shows that annual recurring revenues, number of patents granted, and technical co-founders significantly and positively affect the probability to receive funding or the valuation. In addition, information disclosed by startups about revenue and burn rate are valued by investors.

Keywords

startup valuation, venture capital, software startups, value relevance

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1. Introduction

How to value startups is critical for both early-stage investors and entrepreneurs. From a venture capitalist's perspective, the valuation is an effective means of aligning the interests between the entrepreneur and investor (De Clercq et al., 2006). From an entrepreneur's perspective, securing financing through venture capital is crucial to enable rapid growth.

Startups are typically associated with high risks, high cash burn rates, and asymmetric information and thus difficult to value (Sahlman, 1990; Sievers, Mokwa and Keienburg, 2013). The applicability of commonly used valuation approaches in corporate finance (e.g. discounted cash flow method) is only possible to a limited extent due to strict assumptions and lack of information. In practice, the valuation of startups assessed by venture capitalists like Capnamic Ventures, an early-stage investor based in Cologne, is mainly driven by a holistic assessment based on business-model-specific metrics and relevant information provided by startups. In theory, a gap in the existing literature has been recognized by researchers. Studies of Waldron and Hubbard (1991), Hall and Hofer (1993) and Gompers (1999) summarize the state of knowledge in startup valuation and suggest more in-depth research. This finding is confirmed by Köhn (2018) in a more recent review of the existing empirical literature regarding startup valuation.

This thesis aims to contribute to this research field by performing an empirical analysis of the impact of metrics, used by investors to assess ventures, on the valuation of business-to-business (B2B), software-as-a-service (SaaS) startups and on their probability of receiving funding.

This thesis continues with a theoretical background (chapter 2) on the corporate finance theory and the influence of metrics and information on the valuation of startups. In chapter 3, hypotheses are developed on metrics and information which are expected to affect the startup's valuation and probability of receiving funding. Chapter 4 describes the dataset and methodology. The last chapter critically concludes the findings and classifies them in the scientific and practical context. In addition, limitations and suggestions for future research are provided.

2. Theoretical Background

2.1 Valuation Theory

The theory of corporate finance says that the economic value of every investment is the present value of the related future cash flows (Brealey et al., 2012). This present value of future cash flows can be divided into the present value of net assets in place, based on past investments, and the present value of future growth opportunities (Miller and Modigliani, 1961). The importance of the individual parts shifts during the company's life cycle (Myers, 1977). For example, the value of young firms is mainly a function of the value of growth opportunities, whilst the value of a mature firm is largely attributable to the value of assets in place. This theoretical concept is challenging for the valuation of startups as it requires information that cannot be provided due to low or no revenues, operational losses and short history. Hence, common valuation methods do not work for startups or yield in unrealistic results (Damodaran, 2009).

Economic and strategic management literature provides relevant approaches to predict the firm's development and value creation. The theory of industrial economics takes into account the structure of the market, in which the firm operates, to project the firm's performance (Tirole, 1988). In contrast, the resource-based view focuses on resources and competencies available in the firm (Wernerfelt, 1984). This theoretical framework implies that information about the firm's resources and market opportunities enable the prediction of firm's performance. This concept provides the basis on which venture capitalists and entrepreneurs negotiate the valuation. In this context, the high information asymmetry between entrepreneurs and investors must be considered (Petersen and Rajan, 1995). According to signal theory, startups focus primarily on consciously communicate positive information in order to convey a positive impression.

2.2 Empirical Evidence of Determinants on Startup Valuation

This section presents the most relevant findings and methods used in related studies that provide empirical evidence of determinants for the valuation of startups. Hand (2005) examines the value relevance of financial information for a sample of 204 biotech ventures from the US. The researcher observes that financial statements have a high value relevance for startups financed by venture capital and that their value relevance increases as the firm matures, while the value relevance of non-financial information decreases (Hand, 2005). Armstrong, Davila and Foster (2006) extend the research of Hand (2005) and investigate the relationship between private equity market valuations and financial statement information for a sample of 502 US companies across various industries. Using rank regression analyses, the study shows that costs (e.g. cost of sales, sales, marketing, etc.) incurred by early-stage companies are value enhancing. From a venture capitalists' perspective costs are considered to be value-enhancing investments to generate future cash flows (Armstrong, Davila and Foster, 2006). Sievers, Mokwa and Keienburg (2013) analyse documents from over 200 investment rounds and 127 companies to examine the relevance of financial (balance sheet and income statement items) and non-financial information (e.g. team experience or number of patents) for the valuation of startups in venture capital. The study states that both financial and non-financial information are equally meaningful to the pre-money valuation of startups (Sievers, Mokwa and Keienburg, 2013). Based on the strategic management approach in order to predict the value of startups, Miloud, Aspelund and Cabrol (2012) find that the quality of the founders have a positive and significant impact. Focusing on the internal resources of startups, Hsu (2007) examines the influence of entrepreneurial experience and human capital of startups on their valuation showing that previous entrepreneurial experience increases the valuation of the respective startups. Consequently, this thesis aims to contribute to the literature of value relevance of financial and non-financial information for startups and to apply recent findings to a sample of B2B SaaS startups.

3. Hypotheses Development

In this chapter hypotheses are developed on how financial and non-financial information are expected to affect the probability of receiving funding and the valuation of startups. The results of related studies are provided for each determinant and put into the context of fundraising and valuation of B2B SaaS startups by considering best practices of leading venture capitalists.

3.1 Assets in Place

3.1.1 Technology Asset

Intellectual property is important for early-stage investors as it can further reduce asymmetric information (Block et al., 2014; Greenberg, 2013). Armstrong, Davila and Foster (2006) show that the number of patent applications filed and granted is positively related ($p < 0.05$) to the pre-money valuation of startups. Greenberg (2013) analyses 317 Israeli startups and finds that patent applications are significantly and positively related to firms' valuations across various industries, while they are not relevant to software startup valuations. In this thesis, a positive correlation between the number of patents granted and the valuation of startups is expected, as it signals validation of past investments and increases the defensibility of technology.

H1a: An increased number of patents granted affects positively the probability of receiving funding.

H1b: An increased number of patents granted has a positive impact on the pre-money valuation.

3.1.2 Human Asset

3.1.2.1 Prior founding experience

From a theoretical point of view, previous entrepreneurial experience seems to be crucial for the performance of a startup, as entrepreneurship is linked to a trial-and-error process. In this way, the knowledge that is essential to build successful startups could be gained from previous entrepreneurial experiences (Brüderl, Preisendörfer and Ziegler, 1992). Hsu (2007) finds that entrepreneurs experienced in setting up a startup achieve higher valuations ($p < 0.05$) for their businesses and are more likely to receive venture capital funding ($p < 0.01$) based on a sample of 149 early-stage technology startups. Wasserman (2017) is in line with these observations and shows the relationship between entrepreneurial experiences and higher valuations ($p < 0.05$). In contrast, the study by Gompers et al. (2010) shows that successful serial entrepreneurs do not achieve higher valuations for their businesses. To summarize, a certain amount of entrepreneurial experience seems to have a positive impact on the performance of startups.

H2a: Prior entrepreneurial experience affects positively the probability of receiving funding.

H2b: Prior entrepreneurial experience has a positive impact on the pre-money valuation.

3.1.2.2 Technical Expertise

In software startups, the technical expertise of the founding team is a decisive success factor, especially in the early stages of product development. In this way, highly qualified teams can convincingly signal the quality of the business, as they have attractive opportunities (Bernstein, Korteweg and Laws, 2017). The researchers show that investors are eager to receive information about the team ($p < 0.05$). A survey among 60 venture capitalists conducted by Point Nine (2018), a Berlin-based venture capital fund, shows that the highest rating is assigned to a strong technical co-founder considering early-stage investments. The result shows that venture capitalists are willing to take a high degree of market risk but want to minimize technological risk. Thus, early-stage investors seem to value technical capabilities in software startups.

H3a: A technical co-founder affects positively the probability of receiving funding.

H3b: A technical co-founder has a positive impact on the pre-money valuation.

3.2 Information Asymmetry

High information asymmetry limits access to traditional financing sources (e.g. bank loans), which is the case for most startups (Petersen and Rajan, 1995). In the context of venture capital, investors usually have incomplete and imperfect information about the startups compared to entrepreneurs. The signaling theory states that the informed party (e.g. entrepreneurs) provides observable information to the less informed party (e.g. investors) and discloses information about unobservable information to enhance communication (Spence, 1978). In the fundraising process, the pitch deck of a startup is an important document to disclose information. Since startups can decide what information they want to communicate, they are more likely to reveal only positive information in pitch decks. When investment negotiations take place, investors have access to sensitive information as part of the due diligence process. Investors are expected to penalize startups with a lower valuation if relevant metrics are not disclosed in advance.

H4a: Undisclosed information affect negatively the probability of receiving funding.

H4b: Undisclosed information have a negative impact on the pre-money valuation.

3.3 Financial Information

3.3.1 Revenue

Several related studies reveal a positive correlation between the revenue of a startup and the valuation assigned by early-stage investors. Davila and Foster (2005) observe a positive and significant correlation ($p < 0.05$) between the change in revenues and change in valuation of startups in the US. Armstrong, Davila and Foster (2006) support this finding and show that there is a positive and significant correlation ($p < 0.01$) between the level of revenue and level of private equity value in pre-IPO periods. In addition, Sievers, Mokwa and Keienburg (2013) validate for a sample of German startups that revenues are value relevant. The empirical study shows that revenues have a positive and significant impact ($p < 0.01$) on the valuation.

Venture capitalists, namely Andreessen Horowitz (2015) and Insight Partners (2018) argue that annual recurring revenue (ARR) is a key metric to assess SaaS startups. As higher revenues are related to higher valuations, it is expected to find similar results for B2B SaaS startups.

H5a: Increased ARR affects positively the probability of receiving funding.

H5b: Increased ARR has a positive impact on the pre-money valuation.

3.3.2 Burn Rate

Armstrong, Davila and Foster (2006) examine the relationship between financial statement information and private equity market valuations of venture capital backed companies in the US. The researchers find that higher costs, namely sales, marketing, general, and administrative expenses ($p < 0.05$) and research and development expenses ($p < 0.01$) lead to higher valuations. This result indicates that venture capitalists consider costs as value-enhancing investments (Armstrong, Davila and Foster, 2006). Sievers, Mokwa and Keienburg (2013) show for a sample of German venture-capital backed startups that research and development expenses have a positive impact ($p < 0.10$), but selling, general, and administrative expenses have a negative effect ($p < 0.05$) on the valuation, contrary to the result of Armstrong, Davila and Foster (2006). Early-stage startups do not monitor and report the cost components separately, but in an aggregated metric (burn rate). The burn rate, calculated by subtracting operating expenses from revenues, shows how much money startups burn (Andreessen Horowitz, 2015; Insight Partners, 2018). As the burn rate includes all costs incurred, a value-enhancing effect is expected.

H6a: Increased absolute value of burn rate affects positively the probability of receiving funding.

H6b: Increased absolute value of burn rate has a positive impact on the pre-money valuation.

4. Empirical Analysis

4.1 Dataset and Methodology

In this section, the dataset and applied methodology are illustrated to examine the formulated hypotheses. In the following, the data collection process is outlined, the variables are defined, the dataset is described statistically, and the applied econometric model is explained.

4.1.1 Data Collection

In order to create a dataset of startups with information about financials, metrics, funding rounds, technology assets and human capital, various data sources are used. Financials and specific metrics are the most sensitive data. Thus, Capnamic Ventures' deal flow tool provides the initial dataset. As Capnamic Ventures is an early-stage investor with a strong focus on B2B SaaS startups, only this kind of startups is considered due to potential selection biases. In order to retrieve the corresponding pitch decks, the following filters are applied. *Business* is selected as startups' customer type. In addition, only startups with a subscription-based revenue model are chosen. In a next step, only startups with a SaaS business model are considered. These filters ensure that only B2B SaaS startups are retrieved from the deal flow tool. In total, 679 startups meet these requirements and represent the database as of September 2019.

Relevant data about funding rounds are retrieved from crunchbase.com and pitchbook.com. Since in several cases it is not possible to match the startups with these databases, 238 are excluded. After combining the dataset based on Capnamic Ventures' deal flow tool and fund-raising data, information on human capital and technology assets are gathered. Prior entrepreneurial information of founders are collected from LinkedIn profiles. In addition, information about patents are retrieved from espacenet.com[1]. Finally, the dataset contains information about 441 fundraising attempts based on data of 416 unique B2B SaaS startups.

[1] Database offered by the European Patent Office containing data of more than 110 million patent documents globally

4.1.2 Definition of Variables

In this section, the dependent and independent variables are defined. Venture capital portfolios follow a power law curve, meaning that only a small percentage of venture capitalists' investments yield the majority of the returns. In order to account for this characteristic, a logarithmic transformation is applied to continuous variables. An overview of the summarized definitions of all variables is illustrated in Table A 1 in the appendix.

4.1.2.1 Dependent Variable

This thesis examines the impact of metrics, used by investors to assess startups, on the valuation of B2B SaaS startups and on the probability of receiving funding. From an investor's perspective, the valuation defines the number of shares for an investment. From an entrepreneur's point of view, receiving funding ensures liquidity and enables rapid growth.

The dependent variable *DFundraising* is calculated as a binary variable. The value 0 is set if a startup could not successfully raise external funding and 1 if the startup received external funding. In order to calculate the dependent variable *LNPreMoneyVal*, the pre-money valuation of the successful funding round is assigned to the startup. In a last step, a logarithmic transformation LN(Pre-money valuation) is applied to reduce the skewed distribution of the dataset.

4.1.2.2 Independent Variables

Team & Technology

The human capital variables relate to the founding date of the startup. Thus, entrepreneurial experience gained from operating the startup is not considered. With regards to the technology assets variable, the number of patents granted is related to the fundraising date of the startup.

The group of human capital variables contains specific characteristics of the founding team. The dummy variable *DSerialEntr* is included to examine the impact of prior entrepreneurial experience on the dependent variables. This dummy variable equals 1 if at least one member of the founding team has co-founded a startup before, otherwise 0. In addition, the dummy variable

DCTO indicates whether one member of the founding team fills the role of a technology leader. Only co-founders with job descriptions containing the words “CTO”, “VP Engineering”, or equivalent are considered. The third variable is related to existing technology assets. *LNNumbPat* captures the number of patents granted. These data are highly skewed and thus require a logarithmic transformation. Since many startups do not have any patents granted in early stages, the natural logarithm LN(number of patents + 1) is applied.

Information Asymmetry

In order to examine the effect of information asymmetry, six dummy variables are introduced, having the value 1 if information are disclosed and 0 if not. The variable *DARR* shows, if any information about ARR are given. *DARRGrowth* is related to any indications about the ARR growth rate. *DBurn* captures any information about the burn rate of the startup. The variable *DUnitEcon* considers the disclosure of data about customer lifetime value and customer acquisition costs, showing the attractiveness of the business model. *DTAM* and *DMarketGrowth* are related to information about the total addressable market and the market growth, respectively.

Financial Indicators

The variable *LNARR* is based on the ARR of the latest year in EUR prior to the funding round. In order to account for the high skewness in the data, a logarithmic transformation is carried out by calculating the natural logarithm LN(ARR). The second financial indicator *LNBurn* is the monthly burn rate in EUR at the time of the funding round. The burn rate is calculated by subtracting operating expenses from revenues. Typically, early-stage startups suffer from low revenues and high expenses, thus reporting a negative value for the burn rate. In order to account for these characteristics, the value 0 was set if the burn rate is positive. In a second step, the absolute value of the burn rate enables a logarithmic transformation in order to reduce the skewed distribution. For this purpose, the natural logarithm LN(Burn rate + 1) is used.

Control Variables

The study of Houlihan Valuation Advisors and VentureOne (1998) examines the influence of startup characteristics on the pre-money valuation and finds that the location of a startup is significantly correlated with the valuation. This dataset is potentially biased towards the German-speaking countries as Capnamic Ventures is based in Cologne and has a strong focus on startups operating in the DACH-region (Germany, Austria and Switzerland). Thus, the dummy control variable *DRegion* is added to account for potential differences between startups based in the DACH-region and those headquartered in non-German speaking countries. In addition, the control variable *Age* is included and defined as the years of existence of the startup at fundraising. The reason is that older startups tend to have competitive advantages due to a broader set of resources, valuable experience and established relationships (Finkle, 1998). In order to control for potential time effects, the variable *FundingYear* is included. For each startup a value on a scale from 1 for 2012 to 8 for 2019 is assigned according to the year of fundraising.

4.1.3 Descriptive Statistics of the Dataset

The characteristics of the dataset are summarized and statistically described. Table 1 shows the summary statistics of the dependent variables, control variables and independent variables.

In this dataset, the mean of *DFundraising* is 0.39, referring to the distribution of 268 failed and 173 successful external financing rounds. Thus, 39.2% of the observed fundraising attempts were successful. The pre-money valuations of the startups range from a minimum of EUR 0.15m[2] to a maximum of EUR 59.12m[3] with a median of EUR 6.00m[4]. In contrast, US based software companies in early-stages had a median valuation of USD 25.00m in 2018, indicating the advanced nature of the venture capital market in the US (Pitchbook Data, Inc., 2019).

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[2] The value of EUR 0.15m is calculated by $e^{11.918}$

[3] The value of EUR 59.12m is calculated by $e^{17.895}$

[4] The value of EUR 6.00m is calculated by $e^{15.607}$

With respect to the general characteristics of the startups, 56.9% of the fundraising startups are located in the DACH-region which is mainly due to the fact that Capnamic has a strong network in German speaking countries. Considering the variable *Age*, the 10th percentile shows that in at least 10% of the fundraising attempts, the startups were not more than one year old, whereas the 90th percentile indicates that at least 10% were 6.92 or more years old. The median of the *FundingYear* implies that at least 50% of the fundraising attempts in this sample took place in 2018 (coded as year 7) or 2019 (coded as year 8), showing the increased attractiveness of this business model for venture capitalists in recent years.

Considering technology asset, the 75th percentile of *LNNumbPat* implies that in at least 75% of the fundraising attempts, the startups do not have any patents granted. According to human capital, 59.7% of the founding teams consist of at least one serial entrepreneur, whereas 82.5% have a technical co-founder. The rows 10 to 15 in the Table 1 statistically describe the distribution of information disclosed in the pitch decks of the startups. Overall, in 62.4% of the pitch decks the ARR is reported, while in only 27.4% information about the ARR growth rate is communicated. Considering the financial situation and profitability, 37.9% of the pitch decks contain numbers about the burn rate and 19.7% about the unit economics (customer acquisition costs and customer lifetime value). Information about the market size are disclosed in 68.5% of the pitch decks, whereas only 29.5% have information about the respective market growth rate included.

The ARR range from a minimum of EUR 1.00k[5] to a maximum of EUR 18.00m[6] with a median of EUR 360.05k[7], based on 275 pitch decks. While the maximum burn rate is EUR 358.25k[8], the minimum natural logarithm value of 0 shows that at least one startup had a positive EBITDA.

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[5] The value of EUR 1.00k is calculated by $e^{6.909}$

[6] The value of EUR 18.00m is calculated by $e^{16.706}$

[7] The value of EUR 360.05k is calculated by $e^{12.794}$

[8] The value of EUR 358.25k is calculated by $e^{12.789}$

Table 1: Descriptive Statistics of Variables

Variables	mean	min	max	sd	p10	p25	p50	p75	p90	N
DFundraising	0.392	0.000	1.000	0.489	0.000	0.000	0.000	1.000	1.000	441
LNPreMoneyVal	15.496	11.918	17.895	1.064	14.221	14.893	15.607	16.126	16.706	171
DRegion	0.569	0.000	1.000	0.496	0.000	0.000	1.000	1.000	1.000	441
Age	3.624	0.000	19.167	2.704	1.000	1.917	3.083	4.750	6.917	437
FundingYear	6.796	1.000	8.000	1.235	5.000	6.000	7.000	8.000	8.000	441
LNNumbPat	0.151	0.000	3.401	0.442	0.000	0.000	0.000	0.000	0.693	441
DSerialEntr	0.597	0.000	1.000	0.491	0.000	0.000	1.000	1.000	1.000	439
DCTO	0.825	0.000	1.000	0.380	0.000	1.000	1.000	1.000	1.000	441
DARR	0.624	0.000	1.000	0.485	0.000	0.000	1.000	1.000	1.000	441
DARRGrowth	0.274	0.000	1.000	0.447	0.000	0.000	0.000	1.000	1.000	441
DBurn	0.379	0.000	1.000	0.486	0.000	0.000	0.000	1.000	1.000	441
DUnitEcon	0.197	0.000	1.000	0.398	0.000	0.000	0.000	0.000	1.000	441
DTAM	0.685	0.000	1.000	0.465	0.000	0.000	1.000	1.000	1.000	441
DMarketGrowth	0.295	0.000	1.000	0.469	0.000	0.000	0.000	1.000	1.000	441
LNARR	12.603	6.909	16.706	1.557	10.519	11.562	12.794	13.641	14.403	275
LNBurn	9.618	0.000	12.789	2.996	8.374	9.267	10.384	11.173	11.781	167

sd = standard deviation, p10 = 10^{th} percentile, p25 = 25^{th} percentile, p50 = 50^{th} percentile/median, p75 = 75^{th} percentile, p90 = 90^{th} percentile, N = number of observations

As presented in the Table A 2 in the appendix, the variable *LNARR* is highly and positively correlated with *Age*, implying that older startups are more likely to have a higher ARR. This is in line with the typical life cycle of firms, showing increased revenues from early-stage to maturity. In addition, the missing values indicate the derivation of the dummy information variables from the financial variables. In order to account for this multicollinearity, the regression is conducted in separate specifications.

4.1.4 Econometric Model

The derived hypotheses are empirically tested based on the previously described variables and the dataset. Two linear regression models are conducted in order to assess which metrics and information affect the dependent variables *LNPreMoneyVal* and *DFundraising* individually.

$$DFundraising_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

$$LNPreMoneyVal_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

$DFundraising_i = i^{th}\ observation\ of\ the\ dependent\ variable\ DFundraising\ (i = 1, \dots, 441)$

$LNPreMoneyVal_i = i^{th}\ observation\ of\ the\ dependent\ variable\ LNPreMoneyVal\ (i = 1, \dots, 171)$

$\beta_0 = intercept/constant$

$\beta_1 \ / \ \beta_k = coefficient\ of\ the\ 1^{st} \ / \ k^{th}\ independent\ variable$

$X_{1i} \ / \ X_{ki} = i^{th}\ observation\ of\ the\ 1^{st} \ / \ k^{th}\ independent\ variable$

$\varepsilon_i = error\ term\ for\ the\ i^{th}\ observation$

$k = number\ of\ independent\ variables\ (including\ control\ variables)$

In order to account for the nature of the binary dependent variable *DFundraising* and thus to verify the results of the respective linear regression*,* a logit regression model is applied. Based on the variance inflation factor (VIF) values in the various regressions (see Table A 3 in appendix), multicollinearity is not affecting these regressions as the values are below the acceptable maximum value of 10 (Freund, Wilson and Sa, 2006). As heteroskedasticity cannot be excluded in these models, robust standard errors are applied.

Furthermore, the formulated hypotheses are tested in a hierarchical regression approach. In a first step, the control variables are included. In a second step, the variables *LNNumbPat*, *DSerialEntr* and *DCTO*, representing the human capital and technology assets, are introduced to the model. The different variable sets of the startups' financial and market information are separately added to the model, resulting in two different specifications for each of the two dependent variables. In the first specification (A) the variables, capturing the effect of the disclosure of information about financials and market data, namely *DARR*, *DARRGrowth*, *DBurn*, *DUnitEcon*, *DTAM*, *DMarketGrowth* are entered. The second specification (B) considers the sample of startups, which provide data about ARR and burn rate, in order to assess the impact on the probability of fundraising and the pre-money valuation. Thus, the variables *LNARR* and *LNBurn* are added to the model.

4.2 Empirical Results

The results of the hierarchical multiple linear regressions with the dependent variables *DFundraising* and *LNPreMoneyVal* including the two different specifications are summarized in Table 2. Table A 4 in the appendix shows the results of the logit regressions in form of the average marginal effects for the binary dependent variable *DFundraising*.

Considering the Base Steps in Table 2, which exclusively consider control variables, both models show a low statistical significance with a R^2 of 0.032 at p < 0.01 (F = 5.970) and an adjusted R^2 of 0.025 for *DFundraising*-Model and a R^2 of 0.181 and an adjusted R^2 of 0.167 at p < 0.01 (F = 9.520) for *LNPreMoneyVal*-Model. These R^2 values imply that control variables explain 3.2% of the variation in *DFundraising* and 18.1% of the variation in *LNPreMoneyVal*.

B2B SaaS startups based in DACH-region seem to be less likely to receive funding but achieve higher pre-money valuations compared to those headquartered outside this region. The coefficients of *DRegion* are negative in all regressions of *DFundraising*-Model (hierarchical regressions and in both specifications), but the coefficients are positive in all regressions of *LNPreMoneyVal*-Model. Considering the statistical significance of the control variables, the coefficients of *DRegion* do not show statistical significance in both models, except the Specification B in *LNPreMoneyVal*-Model. The control variable *Age* indicates a negative relationship between startup's age at date of fundraising and the probability to receive funding, whereas it positively impacts pre-money valuation. In *DFundraising*-Model, the coefficients of *Age* are negative in all steps and significant at the 5% and 10% level. With regards to *LNPreMoneyVal*-Model, the coefficients are positive in all steps and statistically significant at the 1% level. The year of fundraising, captured in control variable *FundingYear*, affects the dependent variable *DFundraising* negatively, but dependent variable *LNPreMoneyVal* positively. The coefficients are statistically significant in all steps of both models at the 1% and 5% significance level, with respective positive (*LNPreMoneyVal*-Model) and negative (*DFundraising*-Model) signs.

Table 2: Linear Regression Models

DFundraising (regress)	Base Step	Step 2	Step 3 Specification A	Step 3 Specification B
DRegion	-0.014 (0.048)	-0.005 (0.048)	-0.008 (0.048)	-0.167 (0.094)
Age	-0.017** (0.008)	-0.015* (0.009)	-0.019** (0.009)	-0.030** (0.014)
FundingYear	-0.060*** (0.017)	-0.068*** (0.018)	-0.061*** (0.019)	-0.066** (0.031)
LNNumbPat		0.017 (0.053)	0.008 (0.052)	0.036 (0.091)
DSerialEntr		0.018 (0.048)	0.025 (0.048)	-0.110 (0.085)
DCTO		0.132** (0.056)	0.137** (0.056)	0.107 (0.107)
DARR			-0.028 (0.059)	
DARRGrowth			0.072 (0.063)	
DBurn			0.103* (0.053)	
DUnitEcon			-0.083 (0.063)	
DTAM			-0.015 (0.056)	
DMarketGrowth			-0.017 (0.056)	
LNARR				0.064** (0.030)
LNBurn				0.010 (0.013)
Constant	0.867*** (0.127)	0.794*** (0.136)	0.746*** (0.144)	0.200 (0.451)
N	437	435	435	138
R^2	0.032	0.044	0.058	0.111
Change in R^2 (compared to)	-	0.012 (Base Step)	0.014 (Step 2)	0.067 (Step 2)
Adjusted R^2	0.025	0.03	0.031	0.056
F	5.970***	3.910***	2.400***	2.550**

LNPreMoneyVal (regress)	Base Step	Step 2	Step 3 Specification A	Step 3 Specification B
DRegion	0.166 (0.152)	0.188 (0.155)	0.184 (0.154)	0.468** (0.192)
Age	0.155*** (0.036)	0.159*** (0.038)	0.109*** (0.038)	0.123*** (0.042)
FundingYear	0.164*** (0.055)	0.159*** (0.060)	0.186*** (0.060)	0.148** (0.073)
LNNumbPat		0.333** (0.165)	0.310* (0.162)	0.144 (0.163)
DSerialEntr		0.075 (0.168)	0.092 (0.157)	0.001 (0.215)
DCTO		0.009 (0.295)	0.002 (0.312)	0.442 (0.316)
DARR			0.350* (0.179)	
DARRGrowth			0.231 (0.194)	
DBurn			0.259 (0.158)	
DUnitEcon			0.007 (0.173)	
DTAM			-0.265 (0.180)	
DMarketGrowth			0.091 (0.183)	
LNARR				0.186*** (0.062)
LNBurn				0.023 (0.034)
Constant	13.813*** (0.412)	13.713*** (0.461)	13.453*** (0.464)	11.137*** (1.156)
N	169	169	169	63
R^2	0.181	0.201	0.284	0.506
Change in R^2 (compared to)	-	0.020 (Base Step)	0.083 (Step 2)	0.305 (Step 2)
Adjusted R^2	0.167	0.171	0.229	0.433
F	9.520***	5.420***	5.150***	6.920***

This table shows the coefficient estimates from the linear regressions. Robust standard errors are in parentheses. Statistical significance on the 1% (5%, 10%) level is denoted by *** (**, *) (two-tailed t-test). See Section 4.1.2 or Table A 1 in the appendix for the definition of the variables.

Introducing human capital and technology asset variables to both models in Step 2, namely *LNNumbPat*, *DSerialEntr* and *DCTO*, R^2 rises by 0.012 to 0.044 at p < 0.01 (*F* = 3.910) for *DFundraising*-Model and R^2 rises by 0.020 to 0.201 at p < 0.01 (*F* = 5.420) for *LNPreMoney-Val*-Model. Considering variable *LNNumbPat*, coefficients are positive in both models and all steps, but merely statistically significant at the 5% and 10% level in *LNPreMoneyVal*-Model in Step 2 and Specification A, indicating a positive effect on pre-money valuation of B2B SaaS startups. However, the coefficients do not keep their significance level throughout all steps and specifications in *LNPreMoneyVal*-Model. Thus, hypothesis H1a, assuming a positive relationship between number of patents and probability of receiving funding, cannot be confirmed. But hypothesis H1b, implying that the number of patents granted positively impacts pre-money valuation of B2B SaaS startups, can cautiously be supported. The coefficient of *LNNumbPat*, for instance in Step 2 of the *LNPreMoneyVal*-Model, indicates that a 10% increase in number of patents increases the pre-money valuation by 3.2%[9] on average, holding all other variables constant. The coefficients of variable *DSerialEntr* are positive in both models, except Specification B in *DFundraising*-Model. However, as the coefficients appear to be insignificant, hypotheses H2a and H2b cannot be verified. Hence, no systematic effect of founders' prior entrepreneurial experience on the probability of fundraising or the pre-money valuation is found, considering this sample of B2B SaaS startups. Regarding the variable *DCTO*, the coefficients are found to be positive in both models and all steps, but only statistically significant at the 5% significance level in Step 2 and Specification A of the *DFundraising*-Model. Hence, hypothesis H3a can cautiously be supported, implying that a technical co-founder tends to positively impact the probability of fundraising of B2B SaaS startups. This result is in line with industry practice of leading early-stage investors (Point Nine, 2018). Furthermore, these findings are consistent with the results from the logit regression. According to Step 2 of *DFundraisin*g-Model, a technical co-founder increases the probability of B2B SaaS startups to receive funding by 13.2 percentage points on average, holding all other variables constant.

Adding the information dummy variables to the Base Steps yields Specification A. The introduction of these variables increases R^2 by 0.014 to 0.058, while the adjusted R^2 rises to 0.031 at $p < 0.01$ ($F = 2.400$) for *DFundraising*-Model and increases R^2 by 0.083 to 0.284 with an adjusted R^2 of 0.229 at $p < 0.01$ ($F = 5.150$) for *LNPreMoneyVal*-Model. Regarding the coefficients, only *DBurn* shows statistical significance at the 10% level in *DFundraising*-Model, whereas *DARR* shows statistical significance at the 10% level in *LNPreMoneyVal*-Model. Thus, partial support is provided for hypotheses H4a and H4b, indicating that undisclosed financial

[9] The percentage value of 3.2% is calculated by $e^{0.333\, x \ln(1.1)} - 1$

information about burn rate and ARR have a negative impact on the probability of fundraising and the valuation of B2B SaaS startups, respectively. These findings are consistent with those from the logit regression. The coefficient of *DBurn* in Specification A in *DFundraising*-Model indicates that B2B SaaS startups disclosing information about the burn rate have on average a 10.3 percentage points higher probability of receiving funding, holding all other variables constant. Considering the coefficient of *DARR* in Specification A in *LNPreMoneyVal*-Model, B2B SaaS startups disclosing information about ARR have on average a 41.9%[10] higher pre-money valuation, holding all other variables constant.

Adding variable *LNARR* and *LNBurn* to the regressions in Specification B increases the R^2 by 0.067 to 0.111 with an adjusted R^2 of 0.056 at $p < 0.05$ ($F = 2.550$) for *DFundraising*-Model and increases the R^2 by 0.305 to 0.506 with an adjusted R^2 of 0.433 at $p < 0.01$ ($F = 6.920$) for *LNPreMoneyVal*-Model. The coefficients of *LNARR* are found to be positive and significant at the 1% and 5% level in both models, respectively. These findings confirm the hypotheses H5a and H5b, indicating that increased ARR positively affect the probability of receiving funding and the pre-money valuation of B2B SaaS startups. Furthermore, these findings are consistent with the results from the logit regression. According to Specification B in *DFundraising*-Model, an ARR increase of 10% increases the probability of receiving funding by 0.6%[11] on average, holding all other variables constant. Considering the *LNPreMoneyVal*-Model, the coefficient of *LNARR* implies that a 10% increase in ARR increases the pre-money valuation by 1.8%[12] on average, holding all other variables constant. The coefficients of the variable *LNBurn* are positive in both models, but they appear to be insignificant. Hence, the hypotheses H6a and H6b cannot be confirmed. In consequence, no systematic effect of the burn rate on the probability of fundraising or pre-money valuation is found for B2B SaaS startups.

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[10] The percentage value of 41.9% is calculated by $e^{0.350} - 1$

[11] The percentage value of 0.6% is calculated by $0.064\ x \ln(1.1)$

[12] The percentage value of 1.8% is calculated by $e^{0.186\ x \ln(1.1)} - 1$

5. Discussion

5.1 Classification of Results

As outlined in chapter 2.2, related studies examine the effect of financial and non-financial information on the pre-money valuation. Most of the studies are based on samples of U.S. startups across varies industries, whereas the majority of venture capitalists are focused on specific industries or business models across various countries. Thus, this study contributes to prior research as it examines the impact of information and metrics on the probability of receiving funding and the pre-money valuation of startups with a B2B SaaS model. Hence, metrics, venture capitalists like Capnamic Ventures apply in order to assess software startups, are validated. The results presented in section 4.2 show statistically significant determinants for the probability of B2B SaaS startups to receive funding. Namely, the variables *DCTO*, *DBurn* and *LNARR* appear to positively and significantly impact *DFundraising*. In addition, the variables *LNNumbPat*, *DARR* and *LNARR* appear to positively and significantly impact *LNPreMoneyVal*. Considering both models, *DSerialEntr*, *DARRGrowth, DUnitEcon, DTAM, DMarketGrowth* and *LNBurn* show no statistical significance. Whereas the observed effects of *LNARR* correspond to the formulated hypotheses, further findings must be considered separately.

The variable *LNNumbPat* cautiously confirms the hypothesis, that the number of patents granted has a positive impact on the pre-money valuation of B2B SaaS startups. Thus, supporting the research by Armstrong, Davila and Foster (2006). Patents signal validation of past investments and thus increase the defensibility of a startup's technology. Concerning fundraising, the number of patents does not show a statistically significant impact on the probability of receiving funding of B2B SaaS startups. Thus, venture capitalists do not seem to consider patents granted as a necessary requirement for early-stage B2B SaaS startups. With regards to variable *DSerialEntr*, prior entrepreneur experience does not show a statistically significant impact on the probability of fundraising or pre-money valuation. In order to verify these findings, the track record of serial entrepreneurs should be considered in more detail as the study by Gompers et al. (2010) presents. Variable *DCTO* confirms the hypothesis, that technical co-founders have a positive impact on probability of fundraising. Thus, it indicates that filling key positions by the founding team is a distinct advantage for early-stage software startups in the fundraising process, but not value-enhancing to investors.

Considering the dummy variables of information disclosed in pitch decks, early-stage investors seem to value information about current traction (*DARR*) and investment rate (*DBurn*), but do not care too much about the profitability of the business model (*DUnitEcon*) as well as market data (*DTAM* and *DMarketGrowth*). A possible explanation could be that venture capitalists do not rely on startups' ability to calculate the profitability of their business and to size the market correctly. Thus, these information are considered to be the least verifiable in pitch decks.

In contrast to the result of Armstrong, Davila and Foster (2006), the burn rate is not considered to be value-enhancing for B2B SaaS startups in this sample. As the study of Armstrong, Davila and Foster (2006) is based on a sample of U.S. startups, cultural differences could potentially explain the deviating observations. Thus, venture capitalists in Europe seem to value capital efficiency more than the investment character of high burn rates. This idea is partially supported by Sievers, Mokwa and Keienburg (2013), who show for German startups a positive impact of research and development expenses and a negative impact of selling, general and administrative expenses on the valuation.

5.2 Limitations

While this thesis provides insights about the determinants of the probability of fundraising and the pre-money valuation of B2B SaaS startups, there are some constraints that need to be considered. One potential restriction is that information about revenues and burn rates are based on pitch decks and thus not validated by 3rd parties. Information derived from pitch decks are unregulated and have a “sales” character meaning that all facts stated can be biased towards the goal of the startup. In consequence, this dataset could be skewed due to information asymmetry. Secondly, data about the founding team from LinkedIn could be a limitation. Information on LinkedIn are self-reported and thus these data could be overstated, incomplete or false.

In addition, this dataset shows gaps for some variables as not every variable is observable for every startup. Thus, the number of observations in the different regression model varies from 63 to 437, which lies in the range of related studies. Nevertheless, a larger sample size could increase the representativeness of the sample and the significance of the results.

Lastly, this thesis is based on B2B SaaS startups that approached a German venture capitalist. Hence, the results cannot be generalized across industries, business models and geographies.

5.3 Future Research

Due to limited access to information about startups and in particular validated data, various aspects could not be covered in this thesis. Thus, an extension of this study could provide additional insights for both venture capitalists and entrepreneurs.

In order to address the problem of partly not validated financials, the dataset could be enlarged with data from other venture capitalist to ensure a large and verified dataset of startups, which successfully raised capital from external investors. This approach could not only increase the accuracy of the data, but also the representativeness of the study. As this thesis suggests, early stage investors have a strong focus on information about the current financials, traction, the founding team and the technology in order to derive to the pre-money valuation. Thus, future research could include more specific metrics, e.g. investment expenditures, total revenue in the sales pipeline, churn- and retention rates, team composition, etc. Sending surveys to other B2B SaaS early-stage investors would be one approach to address this challenge, but a low response rate due to the sensitivity of these information has to be critically considered.

Similar to previously mentioned issues, information about the founding team and in particular the technical leader could be obtained by sending questionnaires to founders in order to retrieve accurate and enhanced data on prior educational, entrepreneurial and professional experiences.

6. Conclusion

This thesis examines, which metrics and information, venture capitalists apply to assess B2B SaaS startups, have an impact on the probability of receiving funding and the pre-money valuation. Thus, it contributes to the literature of value relevance of financial and non-financial information for startups. Relevant findings are often based on studies observing U.S. startups across various industries. This work examines the relevance of these results for a sample of 441 fundraising attempts of B2B SaaS startups that approached a German venture capitalist. By having access to pitch decks not publicly available, sensitive metrics and information are evaluated.

Based on the empirical study of 441 fundraising attempts from 416 B2B SaaS startups, various metrics and information are found to significantly impact the fundraising probability and valuation. Considering the assets in place, venture capitalists value patents and a technical co-founder. Both metrics give an indication of the defensibility of the technology, which is crucial for venture capitalists assessing B2B SaaS startups. Overall, early-stage investors penalize startups for not disclosing information in their pitch decks about the traction and financial situation, captured by revenue and burn rate. The results indicate that the ARR is value relevant for early-stage startups, showing a first validation of the business model to investors.

All in all, this thesis serves as a guideline to venture capitalists and entrepreneurs, indicating which metrics and information are value relevant for early-stage B2B SaaS startups.

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Appendix

Table A 1: Overview of Definitions of the Variables

Dependent Variable	
DFundraising	Dummy variable equaling 1 if a startup has successfully raised external capital in a funding round, otherwise 0
LNPreMoneyVal	Natural logarithm of a startup's pre-money valuation (in EUR) at the date of fundraising (LN(Pre-money valuation))
Independent Variables	
DRegion	Dummy variable equaling 1 if a startup is headquartered in DACH-region (Germany, Austria, Switzerland), otherwise 0
Age	Age of a startup in years at the date of fundraising
FundingYear	Categorical variable assigning each startup a value according to its fundraising date (2012 = 1, 2013 = 2, …, 2019 = 8)
LNNumbPat	Natural logarithm of a startup's number of patents granted at the date of fundraising (LN(Number Patents +1))
DSerialEntr	Dummy variable equaling 1 If at least one member of the founding team founded a company before, otherwise 0
DCTO	Dummy variable equaling 1 If one member of the founding team fils the role of a technological leader (CTO), otherwise 0
DARR	Dummy variable equaling 1 if information about ARR is given, otherwise 0
DARRGrowth	Dummy variable equaling 1 if information about ARR growth rate is given, otherwise 0
DBurn	Dummy variable equaling 1 if information about burn rate is given, otherwise 0
DUnitEcon	Dummy variable equaling 1 if information about unit economics (customer lifetime value and customer acquisition cost) are given, otherwise 0
DTAM	Dummy variable equaling 1 if information about total addressable market is given, otherwise 0
DMarketGrowth	Dummy variable equaling 1 if information about expected market growth rate is given, otherwise 0
LNARR	Natural logarithm of a startup's annual recurring revenue (in EUR) in the latest year prior to fundraising (LN(ARR))
LNBurn	Natural logarithm of a startup's burn rate (in EUR) in the latest month prior to fundraising (LN(Burn + 1)); If the burn rate is positive (profit), then 0, otherwise absolute value of the burn rate

Table A 2: Correlation Matrix of the Variables

	DFundraising	LNPreMoneyVal	DRegion	Age	FundingYear	LNNumbPat	DSerialEntr	DCTO	DARR	DARRGrowth	DBurn	DUnitEcon	DTAM	DMarketGrowth	LNARR	LNBurn
DFundraising	1.00															
LNPreMoneyVal	-	1.00														
DRegion	0.01	-0.06	1.00													
Age	-0.10	0.36	-0.20	1.00												
FundingYear	-0.16	0.25	-0.04	0.05	1.00											
LNNumbPat	0.02	0.11	-0.06	0.07	0.00	1.00										
DSerialEntr	0.03	-0.02	-0.07	-0.05	0.01	-0.04	1.00									
DCTO	0.08	0.09	-0.03	-0.08	0.19	0.05	0.05	1.00								
DARR	-0.01	0.33	0.01	0.31	0.00	0.04	0.02	0.05	1.00							
DARRGrowth	0.01	0.27	-0.12	0.36	0.04	-0.05	0.02	0.06	0.46	1.00						
DBurn	0.10	0.20	0.10	0.14	-0.21	0.04	-0.01	-0.03	0.35	0.10	1.00					
DUnitEcon	-0.05	0.11	0.03	0.12	0.00	-0.13	0.11	0.08	0.20	0.28	0.12	1.00				
DTAM	0.00	-0.09	0.01	0.00	-0.01	-0.03	0.07	0.11	0.11	0.10	0.05	0.14	1.00			
DMarketGrowth	0.01	0.05	0.02	-0.01	-0.08	-0.01	0.04	0.07	0.04	0.08	0.05	0.10	0.46	1.00		
LNARR	0.06	0.58	-0.19	0.51	0.06	0.08	-0.01	0.00	-	0.39	-0.02	0.01	0.02	0.07	1.00	
LNBurn	0.01	0.14	0.08	-0.07	0.03	0.20	0.00	-0.03	0.02	0.00	-	-0.05	0.05	0.00	-0.05	1.00

Table A 3: The Variance Inflation Factor Values for the Linear Regression Models

DFundraising	Step 2		Specification A		Specification B	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**
DRegion	1.05	0.952	1.08	0.926	1.13	0.885
Age	1.06	0.943	1.27	0.787	1.64	0.610
FundingYear	1.04	0.962	1.09	0.917	1.08	0.926
LNNumbPat	1.01	0.990	1.04	0.962	1.10	0.909
DSerialEntr	1.01	0.990	1.03	0.971	1.04	0.962
DCTO	1.05	0.952	1.08	0.926	1.10	0.909
DARR			1.49	0.671		
DARRGrowth			1.46	0.685		
DBurn			1.22	0.820		
DUnitEcon			1.15	0.870		
DTAM			1.31	0.763		
DMarketGrowth			1.28	0.781		
LNARR					1.51	0.662
LNBurn					1.08	0.926
Mean VIF	1.04		1.21		1.21	

LNPreMoneyVal	Step 2		Specification A		Specification B	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**
DRegion	1.10	0.909	1.16	0.862	1.21	0.826
Age	1.12	0.893	1.37	0.730	1.89	0.529
FundingYear	1.19	0.840	1.25	0.800	1.34	0.746
LNNumbPat	1.01	0.990	1.07	0.935	1.08	0.926
DSerialEntr	1.05	0.952	1.10	0.909	1.09	0.917
DCTO	1.19	0.840	1.28	0.781	1.28	0.781
DARR			1.60	0.625		
DARRGrowth			1.53	0.654		
DBurn			1.31	0.763		
DUnitEcon			1.15	0.870		
DTAM			1.34	0.746		
DMarketGrowth			1.35	0.741		
LNARR					1.72	0.581
LNBurn					1.17	0.855
Mean VIF	1.11		1.29		1.35	

Table A 4: Logit Regression Model

DFundraising (logit)	Base Step	Step 2	Step 3 Specification A	Step 3 Specification B
DRegion	-0.015 (0.047)	-0.006 (0.047)	-0.008 (0.048)	-0.159* (0.085)
Age	-0.018* (0.010)	-0.017* (0.010)	-0.021* (0.011)	-0.032** (0.015)
FundingYear	-0.058*** (0.017)	-0.067*** (0.017)	-0.060*** (0.018)	-0.065** (0.030)
LNNumbPat		0.018 (0.051)	0.008 (0.049)	0.034 (0.084)
DSerialEntr		0.017 (0.051)	0.024 (0.047)	-0.109 (0.080)
DCTO		0.138** (0.061)	0.143** (0.061)	0.110 (0.106)
DARR			-0.026 (0.058)	
DARRGrowth			0.072 (0.062)	
DBurn			0.102** (0.051)	
DUnitEcon			-0.089 (0.066)	
DTAM			-0.015 (0.055)	
DMarketGrowth			-0.016 (0.055)	
LNARR				0.065** (0.030)
LNBurn				0.009 (0.013)
N	437	435	435	138
Pseudo R^2	0.024	0.034	0.045	0.085
Change in R^2 (compared to)	-	0.01 (Base Step)	0.011 (Step 2)	0.051 (Step 2)
Wald Chi^2	15.040***	19.390***	23.150**	14.040*

This table shows the average marginal effects of the logit regressions. Robust standard errors (estimated by the delta method) are in parentheses. Statistical significance on the 1% (5%, 10%) level is denoted by *** (**, *). See Section 4.1.2 or Table A 1 in the appendix for the definition of the variables.